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THE CIRCULAR EFFECTS OF POPULARITY INFORMATION AND ELECTRONIC WORD-OF-MOUTH ON CONSUMER DECISION-MAKING: EVIDENCE FROM A CROWDFUNDING PLATFORM

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THE CIRCULAR EFFECTS OF POPULARITY INFORMATION AND ELECTRONIC WORD-OF-MOUTH ON CONSUMER DECISION-MAKING: EVIDENCE FROM A CROWDFUNDING PLATFORM

Research in Progress

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Abstract

Potential backers of crowdfunding campaigns often need to make investment decisions based on limited information, as the project they invest in has not come into existence at the time the campaign is running. As a consequence, other evidence for the trustworthiness and quality of a crowdfunding campaign, such as popularity information and electronic Word-of-Mouth (eWOM), are becoming increasingly important. In order to identify interdependencies between these influential factors and the backers' decisions, we deploy the Panel Vector Auto-Regression (PVAR) methodology to estimate impulse-response functions that depict the response of one variable to a shock in another variable. Preliminary results from Kickstarter suggest that a positive shock in popularity information is associated with a higher number of campaign backers in the next period. The same is true for eWOM within the social networks Twitter and Facebook. Despite strong feedback cycles within platforms, our preliminary results show little evidence for cross-platform effects between social media and the number of backers and vice versa. First results show that our current understanding of the impact of popularity information and eWOM on decision making is far from conclusive. We will further validate these findings by extending the dataset, both in time and scope.

Keywords: Popularity Information, Electronic Word-of-Mouth, Informational Cascades, Crowdfunding, Panel Vector Auto-Regression

1 Introduction

Crowdfunding allows individuals to raise funding by receiving contributions from a large number of individuals through an open call on the Internet. The success of crowdfunding platforms such as Kickstarter has made crowdfunding a viable alternative solution for funding a seemingly endless variation of projects, which are presented on the respective platforms as campaigns and are then supported financially by so-called backers. Potential backers of crowdfunding campaigns, however, often need to make their investment decisions based on limited information, as the project they invest in has often not come into existence at the time the campaign is running. Furthermore, there is no legal obligation for the creator of a reward-based crowdfunding campaign to actually deliver the advertised reward to the backer (Mollick, 2014). Fortunately, today's social web offers information that helps prospective backers to evaluate the trustworthiness of a specific crowdfunding project. Popularity

information in the form of the number of backers and messages about the campaign on social media platforms such as Facebook and Twitter are important signals. Consequently, when it is not possible for potential backers to thoroughly evaluate the project's utility before investing in it, it becomes optimal for them to infer the quality from the behavior of preceding supporters. This behavior leads to informational cascades, an information-based explanation for herd behavior that occurs when individuals who face a certain decision choose to follow the actions of others who faced the same decision earlier on, instead of taking a decision based on their own private information (Bikhchandani et al., 1992, 1998; Duan et al., 2009). Crowdfunding offers two potential sources of information that allow informational cascades to occur, namely, the number of previous backers and the eWOM surrounding the campaign. Presumably, these two sources will differ in the magnitude of their influence on the evolvement of informational cascades, as the number of backers is a direct measure of a campaign's success (primary source) and is displayed directly on the crowdfunding platform, whereas the eWOM is an indirect measure (secondary source). Previous research has shown that informational cascades occur regularly on the Internet, especially when adopting goods whose value can only be ascertained after the purchase (e.g., Duan et al., 2009). Similarly, Zhang and Liu (2012) and Herzenstein et al. (2011) have found that in equity- and lending-based crowdfunding markets, individuals tend to contribute to projects that already have a lot of support from the community to reduce their own risk in the face of uncertainty about the proposed new project. Then again, Burtch et al. (2013) have shown that in donation-based markets prior contribution leads to a substitution effect, as potential backer see less "need" to support the specific project. However, it remains unclear what dynamics prevail in reward-based crowdfunding markets and whether positive or negative informational cascades occur. Furthermore, to our best knowledge, no prior work has examined the impact of eWOM on contribution behavior in reward-based crowdfunding markets. Veit et al. (2014) propose a future field of academic interest in the proactive role of consumers and the effects of social recommendations. We therefore gathered data from the crowdfunding platform Kickstarter, to fill this research gap and to answer the following research question:

RQ: Do popularity information and eWOM lead to informational cascades on crowdfunding platforms and is there a circular relationship between them?

2 Theoretical Background and Prior Research

2.1 Crowdfunding

Crowdfunding is built on to the concept of crowdsourcing, which in its core allows individuals or organizations to reach a certain (project) goal by receiving small contributions from a large number of individuals instead of choosing the traditional approach and receiving large contributions from a small number of individuals. Crowdfunding can be seen as a subset of crowdsourcing, enabling project creators to collect relatively small financial contributions from a large number of project backers through an open call—mostly on the Internet (Schwienbacher and Larralde, 2012). It creates a large, relatively undefined network of project stakeholders with diverse intentions and consequently decreases the importance of other investors, such as financial institutes or venture capitalists. The reasons for project creators to choose crowdfunding are manifold and not limited to financial aspects. The success of platforms such as Kickstarter and Indiegogo has also made crowdfunding a tool that enables founders of technological, artistic, or cultural ventures to validate their business or project ideas on a large scale through the outcome of their campaign on the respective platform. A successful campaign does not only enable the creators to finance their venture or project, but it also secures that there is a market for it. This is especially relevant for niche projects that would otherwise not reach the necessary attention. Furthermore, crowdfunding projects do not only require marketing efforts to be successful; the campaigns themselves can also have a certain marketing effect (Burtch et al., 2013; Mollick, 2014; Shane and Cable, 2002). We also see a variety of incentives for backers to "pledge" for a certain crowdfunding campaign. These incentives mainly depend on the return the backers can

expect from their contribution. Returns can either have a material or a rather idealistic or philanthropic nature and can be ordered by their level of complexity and uncertainty (Ahlers et al., 2012; Hemer et al., 2011). The least complex and most certain contribution is a donation, as the backers do not expect any direct return on their investments (donation-based crowdfunding). Most campaigns have at least some option that allows a donation. On Kickstarter, the most common and salient type of return is a so-called “reward” that often allows backers to be among the first customers to receive the product, get exclusive access to special product versions, or get early access to the service offered by the project creator (reward-based crowdfunding). Alongside donation- and reward-based crowdfunding, two other concepts can be distinguished, namely, lending- and equity-based crowdfunding. However, these concepts are far more complex and returns for the backers are less certain.

In our study, we focus on reward-based crowdfunding, as it is by far the most popular concept of crowdfunding, but little empirical research has been devoted to this concept as yet (Mollick, 2014). Compared to donations, rewards have an increased complexity and level of uncertainty, as there are a number of conditions that have to be met before backers can eventually receive the reward. A fundamental condition is that sufficient funds are raised within the pre-arranged campaign runtime. Kickstarter follows an “All or Nothing” (AoN) model and thus only project creators whose campaigns reach the predefined funding threshold will receive the funds. Otherwise all financial contributions will be refunded to the backers and the project is labeled “unsuccessful”. Regardless of whether the funding goal for a specific project is met or not, pledging for it does not guarantee a reward for the backer, as the “pledge” cannot be put on the same level with a purchase, since there is no legal obligation for the project creator to produce and deliver the reward to the backer (Mollick, 2013). The dynamics of crowdfunding are thus somewhat different from those in a traditional e-commerce setting between a seller and a buyer. Backers act as patrons and customers at the same time (Agrawal et al., 2011) and thus have a certain interest in the success of the crowdfunding campaign. Backers can be less certain that they will actually receive the return on their investment and they have less information about the object they are investing in compared to a regular buying situation, in which the product or service already exists and can be inspected thoroughly. The primary source of information for a potential backer is therefore the campaign description the creator has published on the respective platform. This description almost always includes a short video, showing the creator and some sort of prototype or the finished product. Even though this content allows the backer to develop an attitude towards the campaign and the comprised rewards, this attitude is potentially biased due to the fact that it was developed based on a single source of information. Consequently, rewards of crowdfunding campaigns can be seen as experience goods, whose value can only be ascertained by consuming them after the campaign has ended, rather than search goods, whose characteristics and features can easily be evaluated prior to purchase (Nelson, 1970). The quality of the reward thus remains relatively vague at the time the backer decides whether or not to pledge for a specific campaign. We therefore argue that other evidence for the trustworthiness and quality of a campaign becomes increasingly important for the potential backer’s evaluation. More specifically, we distinguish between two potential sources of information, namely, popularity information in the form of the total number of backers and the eWOM in the form of shares the campaign has on Facebook and Twitter. While the total number of previous backers enables the potential backer to infer the success of the campaign directly (primary source), the eWOM is an indirect measure (secondary source). Although there is a growing body of literature on crowdfunding, the role of popularity information, eWOM, and especially the interplay among the different salient indicators in the context of crowdfunding remains largely unexplored. Thus far, crowdfunding itself has mainly attracted academics from disciplines such as finance and entrepreneurship (e.g., Belleflamme et al., 2013; Mollick, 2014; Schwienbacher and Larralde, 2012). A notable exception in the information systems (IS) literature is the empirical examination of social influences of prior contribution behavior by Burtch et al. (2013). However, they examine reinforcement and substitution effects of prior contribution and do not take into account the influence of social media. Furthermore, their work is based on a crowdfunding-market focused on public goods (donation-based crowdfunding) and thus the applicability to other crowdfunding markets is limited.

We therefore intend to advance the current literature by examining the effects popularity information and eWOM have on the outcome of campaigns in reward-based crowdfunding markets.

2.2 Informational Cascades

Informational cascades offer an information-based explanation for herd behavior and occur when individuals who face a certain decision choose to follow the actions of others instead of taking a decision based on their own private information (Bikhchandani et al., 1992, 1998). Such a situation may arise when the individual facing the decision has imperfect knowledge of the product's quality and thus infers the utility by observing the actions of predecessors (Duan et al., 2009). Uncertainty is further increased, when consumers cannot try out products before making purchases (Benlian et al., 2012) and the relationship lacks face-to-face interaction (Benlian and Hess, 2011). Consequently, informational cascades emerge in situations of sequential decision-making and if the actions (but not the decision-making processes) of other individuals are observable (Huck and Oechssler, 2000). These situations may arise frequently on crowdfunding platforms, as the only available source of information is the campaign description the creator has published, which is often limited in scope, imperfect, or biased. Previous research on the effect of prior contribution behavior on the decision-making of potential backers has found that in donation-based crowdfunding markets the "marginal utility contributors gain from giving to a particular project is diminished" (Burtch et al., 2013, p. 501) through the contribution of other backers. The reason is that potential backers see less "need" to contribute as others have already supported the campaign, leading to negative downward informational cascades and ultimately a stagnation of contribution. On the other hand, in equity- and lending-based crowdfunding markets, backers rather invest in projects that already have a lot of support, which signals a superior quality. Consequently, supporting an already successful project becomes a "rational" decision for backers in order to reduce their own risk (Herzenstein et al., 2011; Zhang and Liu, 2012). Hence, already popular campaigns receive a further popularity boost, leading to positive upward informational cascades. To our best knowledge, this effect has not yet been empirically investigated in reward-based crowdfunding markets and it remains unclear whether one can expect positive upward or negative downward informational cascades—or neither. However, we hypothesize that the intentions of backers in reward-based crowdfunding markets are rather similar to those in equity- and lending-based crowdfunding markets as receiving a reward can be seen as the primary objective in all three markets. Consequently, backers try to minimize their risk of pledging without receiving a reward and invest in campaigns that are already successful in terms of the number of backers, leading to a reinforcing effect. We thus expect to identify positive upward informational cascades:

H1: A campaign that receives an increased number of pledges in the previous period will attract additional pledges in the next period.

2.3 Popularity Information and eWOM: A Chicken-and-Egg Problem?

Two research streams with particular relevance to our project are the ones focused on the effects of popularity information and eWOM on consumption behavior, e.g., on subsequent sales performance (Tucker and Zhang, 2011)⁹. Duan et al. (2009), for example, examined the effects of displaying popularity information in the context of online software adoption and found that displaying download counts and rankings for software programs further increases the download counts for already popular software. On the other hand, studies on eWOM were mostly focused on the impact of the volume and credibility of eWOM on sales and other performance indicators (Cheung et al., 2009; Dewan and Ramaprasad, 2012, 2014; Duan et al., 2008; Liu, 2006). This relationship is often not directional, as additional sales may also lead to additional eWOM, creating positive reinforcement effects. However, our understanding of the dynamics that lead to these effects is still far from conclusive. A question that remains largely unexplored in previous research is the simultaneous relationship between popularity

information and eWOM. In other words, do social media shares lead to subsequent pledges by backers or does the number of backers in fact influence the social media shares—or does a bi-directional causality exist? Projects that already have a number of backers are far more likely to be shared on social media compared to projects that do not see any support yet. We thus see the number of backers as the starting point for a potentially circular relationship between the number of backers and the eWOM and infer that:

H2a: A campaign that receives an increased number of pledges in the previous period will attract additional eWOM in the next period.

As consumers often share content for self-representation purposes (Wojnicki and Godes, 2008) consequently positive content may be shared more because it reflects positively on the sender (Berger and Milkman, 2012). Furthermore there is little incentive to share a project in social media giving it higher visibility when intending to produce negative feedback. Therefore it is likely that the quantified eWOM is mainly positive, leading to a complementary hypothesis:

H2b: A campaign that receives an increased number of shares on Facebook and tweets on Twitter in the previous period will attract additional pledges in the next period.

Since it is likely that the social network of an individual user will differ significantly on both social media platforms due to their different purpose and structure—Twitter is modeled as a directed graph, whereas Facebook is modeled as an undirected graph—, we expect to see spillover effects between Facebook and Twitter, as users will potentially share messages they have picked up in one network and share them on the other.

H3: An increased number of shares on Facebook in the previous period will lead to additional tweets on Twitter in the next period and vice versa.

Taking all hypotheses into account, we are able to derive our final research framework (Figure 1).

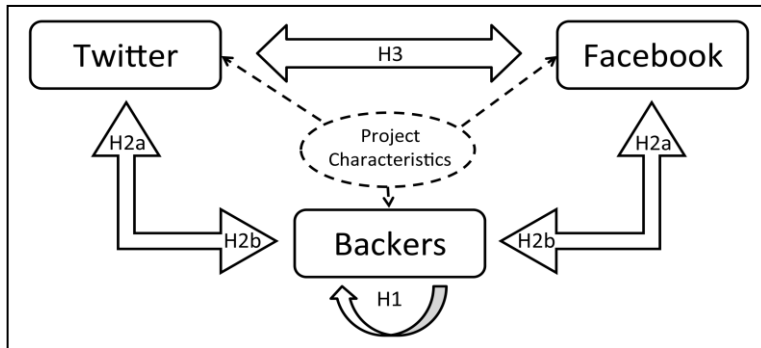


Figure 1. Research Framework

3 Research Methodology

3.1 Model

For our analysis, we employ a panel vector autoregressive approach using daily project level data (Holtz-Eakin et al., 1988). Vector autoregressive models are used to capture interdependencies among multiple time series. The VAR model has proven to be especially useful for describing the dynamic behavior of economic and financial time series and forecasting (Zivot and Wang, 2007). The main challenge of our setup is the simultaneous mutual influence of the different variables of interest, namely, the number of backers and the number of social media shares on Facebook and Twitter. To distinguish the mutual effects and to solve the apparent chicken-and-egg problem, we focus on the orthogonalized impulse-response functions, which show the response of one variable of interest in the

next period (e.g. Facebook shares) to an orthogonal shock of one standard deviation in another variable of interest in the current period (e.g. number of backers). By orthogonalizing the response, we are able to identify the effect of one shock at a time, while holding other shocks constant. This technique combines the traditional VAR approach, which treats all the variables in the system as endogenous, with the panel-data approach, which allows for unobserved individual heterogeneity (Love and Zicchino, 2006). When applying the VAR procedure to panel data, a certain restriction must be imposed. The underlying structure must be the same for each cross-sectional unit. Since this constraint is likely to be violated in practice, usually fixed effects are introduced. As the fixed effects are correlated with the regressors due to the lags of the dependent variables, we use forward mean-differencing, also referred to as the “Helmert procedure” (Arellano and Bover, 1995). This procedure removes only the forward mean and preserves the orthogonality between transformed variables and lagged regressors. We can then use lagged regressors as instruments and estimate the coefficients by a generalized method of moments (GMM) (Love and Zicchino, 2006). The first order PVAR Model is then specified as follows:

$$z_{it} = \Gamma_0 + \Gamma_1 z_{it-1} + e_t \quad (1)$$

where z_{it} is a three-variable vector {BCK, FBS, TW}. The number of backers of a project (BCK) is our proxy for the project’s commercial success. Shares on Facebook (FBS) and tweets on Twitter (TW) represent social media popularity. Γ_0 and Γ_1 represent the matrix functions and e_t the correspondent error term. To analyze the impulse-response functions, an estimation of confidence intervals is required. Since we construct the matrix of the impulse-response function from the estimated VAR coefficients, their standard errors must be taken into account. We therefore calculate standard errors of the impulse-response function and generate confidence intervals with Monte-Carlo simulations. Finally, we also calculate variance decompositions, which show the percentage of the variation in one variable that is explained by the shock of another variable. In our specification we assume that current shocks to the dependent variables have an effect only with a one-day lag.

3.2 Dataset

Our project-level data was collected from Kickstarter, which is among the largest and most prominent crowdfunding platforms on the web and recently announced to have passed \$1 billion in pledges¹. Our dataset includes a total of more than 9,000 projects and a timespan of 25 days, resulting in approximately 100,000 data points. Data on every project available was gathered automatically with a self-developed web crawler to retrieve time-series data of all projects on the website in a daily routine. Additionally, we deployed the application programming interfaces (API) of Facebook and Twitter in order to collect daily data points for the number of shares and tweets a specific campaign had received. We started to collect data in November 2013. Our dataset includes projects from 85 countries, while the majority is from the United States and the United Kingdom. Still, for our current analysis, we only include projects we could observe from their beginning, to eliminate variations during a project’s lifecycle, resulting in 7058 projects and 73,832 observations. No other filtering mechanisms were applied. We also do not expect any fake or untruly projects due to a restrictive review process of each project by Kickstarter specialists².

¹ <https://www.kickstarter.com/1billion>

² <https://www.kickstarter.com/help/faq/creator+questions>

4 Preliminary Results

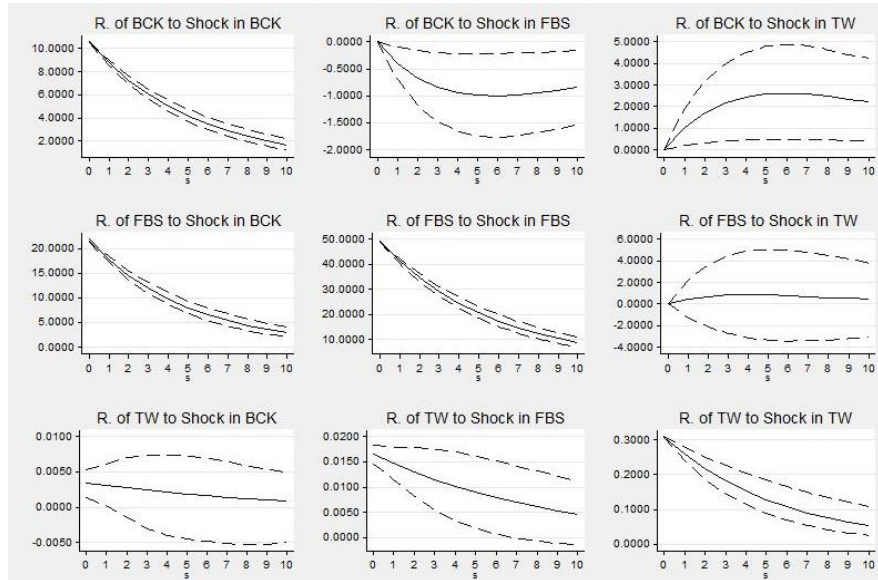
To test our research hypotheses, we estimated the coefficients of the system given in (1). To check for robustness, we ran our analysis with different time lags and received similar results. Table 1 shows summary statistics and preliminary results with our three dependent variables (BCK, FBS, TW).

| Summary statistics | | | |
|--------------------|------------------|------------------|------------------|
| | Mean (SD) | Min | Max |
| BCK | 69.8 (291) | 0 | 10486 |
| FBS | 246.0 (899) | 0 | 51662 |
| TW | 0.4 (5) | 0 | 286 |
| Response of | Response to | | |
| | BCK (t-1) | FBS (t-1) | TW (t-1) |
| BCK | 0.85**** (0.013) | -0.01** (0.001) | 3.32* (1.696) |
| FBS | -0.04 (0.025) | 0.84**** (0.012) | 1.41 (3.389) |
| TW | -0.00 (0.000) | -0.00 (0.000) | 0.84**** (0.037) |
| N obs | 73,832 | | |
| N Projects | 7,058 | | |

Note: **** p<0.001, *** p<0.01, ** p<0.05, * p<0.1 Reported numbers show the coefficients and SE of regressing the row variables on lags of the column variables. Heteroskedasticity-adjusted t-statistics are in parentheses.

Table 1 Summary statistics and main results for PVAR Model estimated by GMM.

We observe a strong positive response of all three variables to one standard deviation shock of their own previous value. The positive and significant response of BCK to BCK (t-1) strongly supports our first hypothesis, identifying positive upward informational cascades. Furthermore, we observe a weak but significant negative response of BCK to a shock of FBS in the preceding period. This result is rather surprising, as we would have expected a positive response, as stated in H2b. This result suggests a possible crowding out effect on Facebook, which calls for further investigation. Shocks on Twitter, on the other hand, are met with a positive and significant response in the backer count, suggesting a reinforcing relationship, weakly supporting H2b for the Twitter platform. Surprisingly, we see no evidence to support H2a and H3 in our sample, which leads us to the conclusion that the ties between social media websites and other platforms are rather weak and one-directional. Graphs of the impulse-response functions with 5% error bands and 10 periods as time span generated by Monte-Carlo simulations are presented in Figure 2. The graphs illustrate the response of a dependent variable in the next 10 periods to a shock in another dependent variable in the preceding period. All responses, except BCK on FBS, are positive but vary in their significance and further highlight the strong reinforcing effect within platforms.



Note: Errors are 5% on each side generated by Monte-Carlo with 1000 repetitions

Figure 2. Impulse responses for 1 day lag of 3 variables: BCK, FBS, TW

Variance decompositions for the different models, presented in Table 2, are in line with the results from the impulse-response functions, showing that most of the variance within the dependent variables is explained by their own value, suggesting a very strong feedback loop within the different platforms, rather than across them. This leads to the conclusion that overcoming a chicken-and-egg problem on one platform does not guarantee an answer to the problem on another platform. Furthermore, these results dilute the expected marketing and spillover effects of eWOM and popularity information.

| | BCK | FBS | TW |
|-----|-------|-------|-------|
| BCK | 86.8% | 1.7% | 11.5% |
| FBS | 14.9% | 85.0% | 0.1% |
| TW | 0.0% | 0.4% | 99.6% |

Table 2 Variance decomposition: Percent of variation in the row variable (10 periods ahead) explained by column variable.

5 Further Research and Expected Implications

First and foremost, our result should be viewed with caution, as our data gathering process is far from complete. Our current sample only includes 25 days of data, which is less than an average project cycle on Kickstarter. Furthermore, we have not yet differentiated project categories or other possible systematic effects. Still, we believe that we are opening up a promising research avenue, improving our understanding of social media, platform interaction and the crowdfunding phenomenon. First results have shown that our current understanding of the impact of popularity information on decision-making is far from conclusive. We intend to extend our current understanding of the circularity of popularity information and social media influence both within and across platforms to fully answer our proposed research question. Promising future research fields are comparisons of different project categories, life-cycle statuses, profit orientations, funding platforms, project sizes, and individual investment amounts. We therefore believe that further studies will contribute new insights into whether and why information spreads within or between platforms and how it ultimately affects consumer decision-making.

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